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Handling Stochastic Occupancy in an Economic Model Predictive Control Framework for Heating System Operation in Dwellings

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Abstract

This paper investigates the effect of integrating a proposed time inhomogeneous occupancy model in an Economic Model Predictive Control framework. Utilizing Model Predictive Control when planning the operation of the HVAC systems enables thermal conditioning based on information regarding the current occupancy and predictions of future occupancy. Performance evaluation of the proposed occupancy model is based on simulations of a one-bedroom apartment subject to stochastic occupancy derived from real-world CO_2 measurements. The simulation results suggest that an occupancy model with a sub-hourly temporal resolution reduces occupancy prediction errors compared to an hourly temporal resolution. The consequences of this are significantly reduces thermal comfort violations but only minor cost savings.

Keywords - Economic Model Predictive Control; Stochastic Occupancy; Occupancy Prediction; Markov Chain

1. Introduction

The thermal indoor climate of a building and, consequently, the need for heating, ventilation and air conditioning (HVAC) is highly affected by the internal heat gains generated by the metabolism of the occupants and their use of electrical equipment [1]. The common way to integrate occupancy information in HVAC control systems is to repeat a static 24-hour schedule. However, static schedules do not capture the stochastic nature of people, which may lead to uncomfortable thermal conditions or waste of energy because HVAC systems maintain thermal comfort in unoccupied building zones [2, 3]. One way to consider the stochastic nature of occupant presence in HVAC operation is to implement real-time occupancy detection, which has demonstrated to reduce energy consumption and uncomfortable thermal indoor climate conditions [4]. However, due to the thermal time-delay of the building first arrived occupants may experience uncomfortable thermal conditions. Furthermore, when awaiting the departure of the last occupant the thermal storage in the building mass is not fully exploited. The concept of Model Predictive Control (MPC) is able to accommodate this. MPC uses a model of the building dynamics together with predictions of the disturbances acting on the building to optimize the HVAC operation by minimizing a cost function [5]. MPC is thus able to include information regarding the current occupancy and predictions of future occupancy for optimal HVAC operation.

The development of occupancy models with the objective to imitate realistic occupancy was first designed for building simulations tools [6, 7]. Page et al. [8] proposed a two-state time inhomogeneous Markov chain model, assuming that the probability of occupant presence satisfies a first order Markovian property, i.e. the future state at discrete time-step $k+1$ only depends on the current state at discrete time-step k. The assumption of a first-order Markovian property is also employed to model occupant presence patterns for employees in an office environment [9]. The model was defined as a generalized linear model based on a time inhomogeneous Markov chain, which captured the two-peak distribution of occupancy and demonstrated similar mean occupancy as the observations.

The integration of a Markov chain based occupancy model in a MPC framework has been proposed by Dobbs and Hencey [10]. In their study, the integration of occupancy prediction yielded an energy saving potential of 31-44% compared to a baseline controller when considering very simple fabricated occupancy profiles. The same authors extended the methodology by implementing an automatic-trained Markov chain occupancy model, based on real occupancy data from an office building [4]. The proposed method uses fractional occupancy for each time-step to increase the precision of the occupancy prediction. However, a fraction of 0.5 (equivalent to 30 minutes with a time-step of 1 hour) do not inform whether the occupants stayed in the first or last part of the time-step or if the stays fluctuated throughout the time-step. The length of the occupancy period and the number of occupancy fluctuations has been shown to affect the MPC controller significantly [11], causing up to 25% difference on the total energy consumption.

1.1 Main Objective and Outline

This paper reports on a simulation-based investigation of the performance of an economic MPC which includes occupancy detection and predictions for optimal heating system operation of a one-bedroom apartment. The concept is similar to the one suggested by Dobbs and Hencey [4] but the case is rather different. Furthermore, instead of using binary hourly values or hourly percentages of occupancy it is investigated whether an occupancy model with a sub-hourly temporal resolution improves the performance of the concept.

2. Markov Chain Occupancy Model

The occupancy model is a two-state first-order Markov chain model [8], which at every discrete time-step k yields a binary value of either X_k=0 or X_k=1 indicating vacancy or occupancy, respectively. The probability of continuing or changing state is dependent of the time of day k and the current state X_k and is collected in a time inhomogeneous right stochastic matrix (1). Since the sum of each row is one, only estimates of p_{01} and p_{10} are required. It is assumed that the transition probabilities are periodic with a period of 24-hours but a distinction between workdays and weekends are made.

$$T_k = \begin{bmatrix} p_{00}(k) & p_{01}(k) \\ p_{10}(k) & p_{11}(k) \end{bmatrix} \quad (1)$$

The estimates of the transition probabilities follows a binomial distribution with two outcomes, where *N* is the total number of detections and *Ns* is the number of successes that indicates state transition (2).

$$f(N, Ns, \theta) = \binom{N}{Ns} \theta^{Ns}(1-\theta)^{N-Ns} \quad (2)$$

If the total number of observations *N* and the number of successes *Ns* is known, the Maximum Likelihood (ML) estimate of θ is simply the proportion of *Ns*. The estimate of p_{01} only updates if the zone changes from vacant and p_{10} only changes if the zone was occupied. The initial estimate of the transition matrix entries is the identity matrix, implying that the best guess of the future state is the state in the current time-step, which has demonstrated satisfying results when used in a MPC framework [3]. The estimates of θ are updated at each observation instant as it is interconnected with real-time sensor-data based occupancy detections established by tracking the trajectory of CO_2-concentration measurements [12].

As the number of occupancy detections increases the importance of each observation decreases which may render the occupancy detection unable to adjust to changing occupancy usage. To investigate whether this affects the performance of the occupancy model a moving window is introduced which neglects observations that are older than the size of the moving window, i.e. enabling the occupancy model to maintain its flexibility and to adjust to changes in room usage.

2.1 Occupancy Prediction

Two methods are tested to evaluate which method makes the most reliable predictions of future occupancy: the Expected Occupancy (EO) or the Inverse Function Method (IFM) [8]. The expected occupancy is computed by the general setting of a time inhomogeneous Markov chain, hence $P(X_{k+r} = i \mid X_k = j)$ is determined by calculating the (j,i)'th entry of the matrix product $T_{k+1} \cdot T_{k+2} \cdot \ldots \cdot T_{k+r}$, where T_k is the time inhomogeneous transition matrices at discrete time-step *k*. The expected occupancy is in general the best guess of the future occupancy; however, this method lacks the ability to handle stochastic occupancy. For instance, if the current state $X_k = 0$ and the transitions probabilities equals $p_{00} = 0.6$ and $p_{01} = 0.4$, the method of expected occupancy yields $X_{k+1} = 0$, i.e. neglecting the rather large 0.4 probability of $X_{k+1} = 1$. The IFM method is used to reproduce the stochastic nature of occupancy [8]. At each time-step, the transition probabilities are cumulated and a random number is drawn from a uniform distribution determining the future state X_{k+1}. This approach tries to capture the stochastic nature of occupancy, with offset in the historical detections.

3. Economic MPC Formulation

The objective of the economic MPC controller (3) is to determine the optimal control input *u* for the heating system by minimizing the total operational cost for a finite future time horizon *H* based on predictions of the energy price *f*. At discrete time-step *k* the optimization problem is solved based on measurements of the current state, a model of the building dynamics, and predictions of the disturbances. The first control input of the optimized control plan is then applied to the building heating system. At next discrete time-step *k+1* the optimization problem is solved again where a new measurement of the states is taken, and the prediction horizon is shifted by one time-step. This receding horizon approach introduces feedback to the system.

$$\min_{u_0 \dots u_H} \sum_{k=0}^{H} f_k \cdot u_k \tag{3a}$$

$$\text{s.t.} \quad x_{k+1} = Ax_k + Bu_k + Ed_k \tag{3b}$$

$$y_k = Cx_k \tag{3c}$$

$$0 \leq u_k \leq P_{max} \tag{3d}$$

$$T_{min,k} \leq y_k \leq T_{max,k} \tag{3e}$$

The model of the building dynamics is defined as a discrete-time Linear Time Invariant (LTI) system described on state-space form (3b) with state matrix *A*, system states x_k, input matrix *B*, control inputs u_k, disturbance matrix *E* and disturbances d_k. The indoor air temperature (*Ti*) is the controllable system state y_k (3c) with output matrix C. The constraints on *Ti* is a function of the predicted occupancy and thus the requirement to maintain a comfortable thermal indoor climate when the room is occupied (3e). The control input is constrained by the maximum design power of the heating system (3d).

4. Simulation

To demonstrate the efficacy and to evaluate the difference between the occupancy prediction methods, simulations concerning the optimization of the operation of the heating system for a one-bedroom apartment were used. The one-bedroom apartment has a floor area of 3.4m x 5.7m, a room height of 3m and a south-facing window. It is located in a well-insulated new building designed to comply the Danish Building Regulation 2015 [13]. For further detailed information on the one-bedroom apartment, see [14].

The co-simulation tool Building Controls Virtual Test Bed (BCVTB) [15] was used to link an EnergyPlus model that represented the true apartment to the economic MPC programmed in MATLAB. The state-space model of the building dynamics (3b) was established as a two-state grey-box model [16] discretized at a time-step of 60 seconds. Note that the importance of the building dynamics model and model-mismatch is not considered in this paper. The simulations were carried out for a period of 45 days using hourly historical weather data from Copenhagen, Denmark and Nord Pool Spot electric prices [17]. To ease the evaluation of the different approaches of occupancy prediction, perfect forecasts of the weather and electricity prices were assumed. A finite future time horizon H of 6 days was chosen to exploit the full potential of the thermal mass. The time-step for which a new control input was send to the heating system (tsCI) varied between 30 or 60 minutes. The time-step of the occupancy model (tsOM) and the length of the moving window (MW) were varied to evaluate their importance. The temperature constraints were defined as 21°C - 24°C when occupied and 19°C-26°C when vacant. For workdays the static 24-hour schedule was defined as occupied from 00:00 to 08:00 and 17:00 to 00:00 and constantly occupied during weekends.

4.1 Real-World Occupancy Profiles

The simulations were performed for four different occupancy profiles that differed greatly due to the stochastic nature of the occupants. The occupancy profiles were established based on real-world CO_2-measurements from four apartments. The CO_2-measurements are transformed to binary occupancy schedules according to the method presented in [12] and assumed to be the actual occupancy (the ground truth). The total number of transitions from vacant to occupied, and the total time-of-use during the simulation period of 45 days for each apartment is listed in table 1.

Table 1 Inspection of real-world occupancy profiles

	Total number of transitions from vacant to occupied [times]	Total occupied time during the simulation period [hours]
Apartment 1	62	336.8
Apartment 2	80	589.1
Apartment 3	68	829.7
Apartment 4	49	728.7

Table 1 illustrates a significant difference between the four occupants and thus the need for an occupancy model that is able to handle stochastic occupancy.

Histograms of vacancy and occupancy intervals are displayed in Fig. 1. The histograms also emphasizes the divergent occupancy profiles for each apartment. It is remarked that for apartment 1 a bin for vacancy interval 10000-10050 minutes with probability 0.016 is omitted from the chart because of readability.

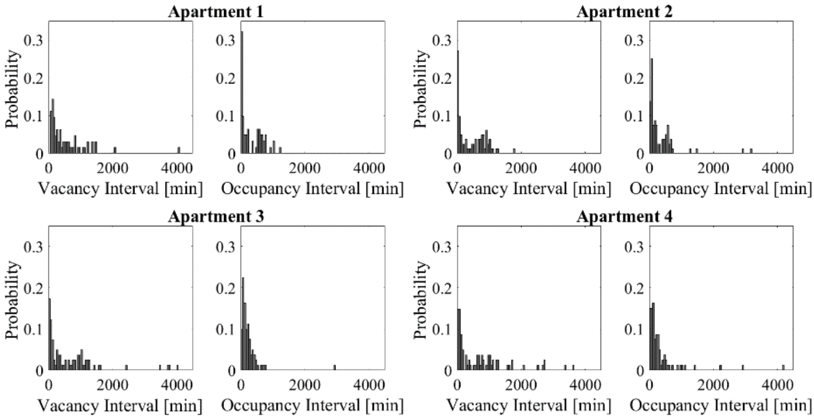

Fig. 1 Histograms of real-world occupancy profiles

5. Results and Discussion

First, the performance of the occupancy model is assessed. Secondly, the potential for achieving cost savings and reducing thermal discomfort is presented for the economic MPC controller where the influence of the occupancy model's temporal resolution and the impact of utilizing a moving window are investigated.

5.1 Occupancy Prediction

To assess the performance of the occupancy prediction methods EO and IFM, the mean absolute error (MAE) of the predictions was calculated. Fig. 2 displays the MAE for apartment 4 as a function of the future prediction time-step and for three occupancy model time-steps tsOM. The charts indicate that the EO method leads to fewest predictions errors compared to IFM. Furthermore, Fig. 2 illustrates that the amount of false vacancies differs the most and that IFM generally underestimates periods of occupancy, potentially resulting in thermal comfort violations. Fig. 2 also shows that the EO method captures the anticipated periodicity of occupancy presence better.

Consistently for all four apartments, the EO method yields the most exact occupancy predictions. However, for apartment 2, which according to table 2 represents the most fluctuating occupant presence, the performance is very similar.

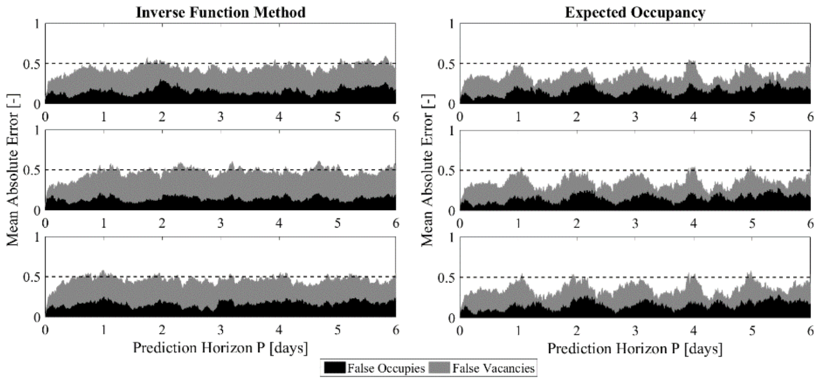

Fig. 2 Mean absolute prediction error. Top (a): tsOM = 60 min. Middle (b): tsOM = 15 min. Bottom (c): tsOM = 5 min.

The performance evaluations indicate that the IFM results in too fluctuating occupancy predictions. Analyzing the result for all four apartments showed that an occupancy model time-step of 15 minutes leads to the fewest predictions errors. The IFM is a stochastic method since it depends on a random number generator; thus, the prediction is one realization out of many. Therefore, five simulations using IFM is performed and the mean result is presented here.

5.2 Economic Model Predictive Control

The aim, when integrating an occupancy model, is to improve the performance compared to using static occupancy schedules; hence, results obtained with static schedules constitutes the performance benchmark. The deviation with respect to operational cost and thermal discomfort is calculated as stated in (4) and (5) respectively, and are displayed in Fig. 3.

$$\Delta\, Operational\ Cost = \frac{\int_0^P E \cdot f\, dt - \int_0^P E_{sch} \cdot f\, dt}{\int_0^P E_{sch} \cdot f\, dt} \tag{4}$$

where P is the total simulation period of 45 days, E is the energy use of the investigated method, f is the energy price and E_{sch} is the energy consumption using occupancy schedules.

$$\Delta\, Thermal\ discomfort = \frac{\int_0^P D_T\, dt - \int_0^P D_{T,sch}\, dt}{\int_0^P D_{T,sch}\, dt} \tag{5}$$

where D_T is the thermal discomfort of the investigated method and $D_{T,sch}$ is the thermal discomfort using static occupancy schedules. The thermal discomfort is the sum of violations of the lower and upper temperature bounds, for both occupied and vacant time-steps.

The *Performance Bound (PB)* constitutes the maximum theoretical savings potential, i.e. perfect occupancy predictions. A great potential for reducing thermal comfort violations is observed for all four apartments with a maximum reduction of approx. 85% (should be 100% if no model mismatch was present). The potential for operational cost savings is limited (maximum of approx. 4%).

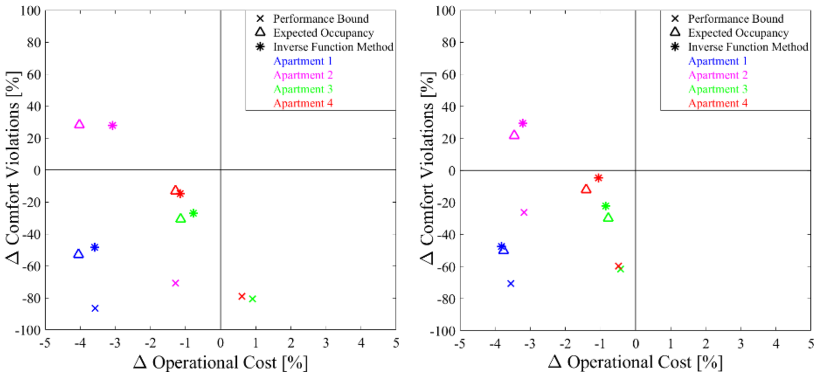

Fig. 3 Results with tsCI = 60 min and MW = 14 days.
Left (a): tsOM = 5 min. Right (b): tsOM = 60 min.

A maximum reduction of approx. 50% of thermal violations is obtained when integrating an occupancy model that utilizes either EO or IFM. Generally, EO is slightly better than IFM. For apartment 2 proper predictions of occupancy were not achieved causing approx. 30% increase of comfort violations compared to implementation of static schedules.

Fig. 3 also shows that the potential for cost savings and thermal discomfort reduction is affected by the temporal resolution of the occupancy model. To examine the importance of the occupancy model time-step closer, Fig. 4 (a) displays the relative savings potential compared to a temporal resolution of 60 minutes. Generally, a finer temporal resolution enables the occupancy models to handle more stochastic occupancy presence thus reducing thermal discomfort. However, Fig. 4 (a) stresses the same tendency as demonstrated in section 5.1, i.e. that a temporal resolution of 15 minutes yields the least occupancy prediction errors and therefore leads to fewer thermal comfort violations. To evaluate the importance of the moving window (MW), an occupancy model without a MW is taken as reference and the difference for a model with a MW length equal to 21 days and 14 days is illustrated in Fig. 4 (b). The results shows that applying a moving window and the length of the window affected the potential discomfort reduction. The results suggest that a length of 14 days was too short; hence, better performance was achieved with a length of 21 days. However, a clear tendency is difficult to observe and further investigations are necessary.

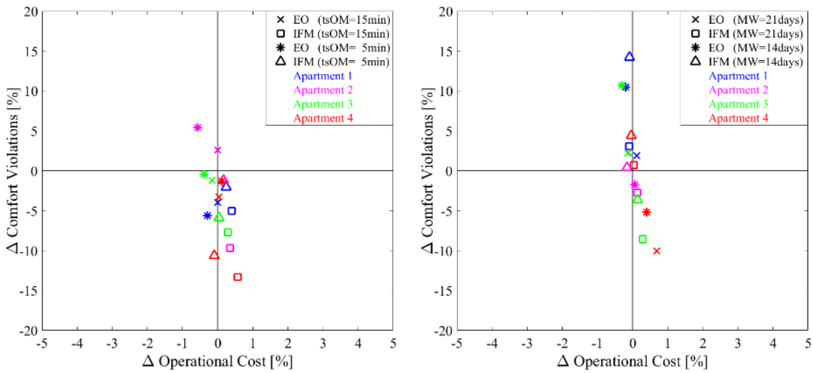

Fig. 4 Left (a): Importance of occupancy model time-step. tsCI = 60 min / MW = 14 days
Right (b) Importance of a moving window. tsCI = 30 min / tsOM = 5 min

6. Conclusion

The proposed occupancy model for handling stochastic occupancy in an economic model predictive control framework for heating system operation in dwellings demonstrated a capability to make reliable predictions of occupant presence for four apartments with very different occupant profiles. The performance evaluation suggests that a temporal resolution of 15 minutes leads to fewer prediction errors compared to an hourly temporal resolution. Furthermore, the results suggest that the EO method should be preferred compared to using IFM, because IFM provides too fluctuating occupancy schedules when used for HVAC control.

Results from test case simulations of the economic MPC framework including the proposed occupancy model suggest a potential for cost savings and thermal discomfort reduction compared to an economic MPC controller that utilizes static occupancy schedules. The results also indicate that an occupancy model with sub-hourly time-step achieves better performance than models with an hourly resolution. No clear impact of applying a moving window was observed. Future work include: i) Using an equivalent sub-hourly temporal resolution in the occupancy model and the optimization problem, thus enabling better handling of stochastic occupancy, but still only forwarding an hourly control input to the heating system by constraining the optimized control input to be equivalent for every hour. ii) Further investigations of the EO method. Currently, a transition probability of 0.5 is used to decide when a state transition is expected; however, this parameter can be increased to provide conservatism to the prediction of occupancy transition. iii) Applying the Markov chain transition probabilities in a stochastic optimization problem.

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